Caveat Venditor - Crowded Exits

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ABSTRACT

Crowded exits arise in stocks where short-sellers hold large positions relative to normal trading volume, and when a catalyst prompts short-sellers to cover their positions rapidly and simultaneously. Where short-covering is large compared to normal trading volume, we would expect upward pressure on the stock price. Using a stock lending database for up to 681 stocks listed on the London Stock Exchange from 1 September, 2003 to 31 May, 2007, we find that crowded exits are associated with positive abnormal returns. This result is both statistically and economically significant. Short-sellers who cover their positions rapidly avoid losses, indicating that they are well informed. Those that fail to cover suffer significant losses.

1. Introduction

The study of short-selling constraints and their impact on market efficiency has been a popular area of research for over thirty years. The literature identifies two types of short-selling constraint: 'direct' and 'indirect'. Direct constraints include legal restrictions on short-selling and the cost of borrowing stock, and are relatively simple to identify and understand. By contrast, indirect constraints have proved to be less tractable. D'Avolio (2002) and Nagel (2005) call for greater research into the nature and impact of indirect short-selling constraints. Geczy *et al.* (2002) argue that if short-selling problems explain the availability of factor portfolio returns to unskilled managers, then these short-selling problems are not borrowing costs, but perhaps liquidity constraints. In this paper we consider *crowded exits*, an indirect constraint on short-selling. Crowded exits have yet to be examined in the literature, and this study fills this gap. Crowded exits arise in stocks where short-sellers hold large positions relative to normal trading volume, and when a catalyst prompts short-sellers to rapidly and simultaneously cover their positions. Catalysts include, but are not limited to, public news releases by companies. The temporary excess of demand for stock relative to normal trading volume leads to upward pressure on the stock price and these events are associated with losses to short-sellers that are economically and statistically significant. As such, the risk of a crowded exit represents an indirect constraint on short-selling. In this paper, we examine a large, stock lending database for conditions where liquidity constraints impact on short-sellers.

As part of any taxonomy of crowded exits, it is helpful to explain how a short position might become 'crowded' in the first instance. One possible scenario is outlined below. Initially, one or more traders with negative information about a company short-sells stock in that company. This represents informed trading and leads to an increase in the number of shares shorted. This increase in short-interest is made public, as most developed stock markets require the publication of data on short-selling or stock lending, in the interests of transparency. A substantial body of empirical research shows that heavily shorted stocks perform poorly (Dechow *et al.*, 2001, Angel *et al.*, 2003, Gopalan, 2003, Ackert and Athanassakos, 2005, Diether *et al.*, 2008 and Boehmer *et al.*, 2008). Market participants who are aware of this literature can simply short-sell stocks that are seen to be heavily shorted, in an attempt to benefit from the short-sellers' information. This is an 'imitation strategy', other examples of which are described in Fligstein (1996, 2001), White (1981, 2001) and Mackenzie (2006). In so far as this imitation strategy occurs in markets, it follows that heavily shorted stock positions contain both informed traders and noise traders. Imitation strategies, however, contain the seeds of their own destruction. In this illustration, imitation leads to an increase in the size of the short position relative to the liquidity of the stock. A crowded position thus develops, based on a mix of 'informed short-selling' and 'rational imitation'.

We refer to short positions that are large relative to normal trading volume as 'crowded positions'. With a catalyst, rapid and simultaneous short-covering can commence and the crowded position becomes a 'crowded exit'. The idea is akin to the audience in a crowded theatre rushing to a narrow exit door once the fire alarm sounds…only so many can leave the building in any given interval of time. A variety of catalysts for a crowded exit are possible: a company could release new, positive information to the market; a sell-side analyst could upgrade his earnings forecast or trading recommendation on a stock; or informed short-sellers could receive new, private information and start to cover their positions, to be followed by imitators. A further catalyst could be that short-sellers become *unable* to hold on to their short positions. This could be due to stock loan recall, client redemptions, margin calls or the rigid application of risk control mechanisms. The resulting short covering could be misconstrued as informed buying, leading imitators to cover their own positions. Finally, manipulators buying shares in a company could prompt short covering amongst traders who misinterpret the manipulative trades as informed buying. From interviews with practitioners, we find that short-sellers perceive crowded exits to be risky: it could become difficult to cover a short position when desired, or the short-seller could suffer losses due to 'market impact' when demanding liquidity to cover a short position quickly.

We study instances of crowded exits by making use of a relatively new commercial stock lending database for up to 681 stocks listed on the London Stock Exchange from 1 September, 2003 to 31 May, 2007. The main findings of this research are as follows: crowded exits are associated with positive abnormal returns (i.e. losses to short-sellers) of up to 27% over a period of 60 days, and this result is both statistically and economically significant. We infer that short-sellers thus face an important indirect constraint on short-selling in the form of crowded exits. New, long-only investors would generally find it difficult to exploit this finding by buying into crowded exits, as by definition these are illiquid positions; however, incumbent short-sellers, unable to readily cover their positions, suffer losses.

2. Data

2.1 Data Sources

We create a new dataset for the purposes of this research by merging data from two sources. The first of these is a commercial database of UK stock lending data from Index Explorers Ltd[1]. This contains daily information on stock lending starting on 3 September, 2003 when the database came into existence. At inception, this database included stocks from the 350 largest companies traded on the London Stock Exchange. The data is largely sourced from CREST — the organisation responsible for settlement of all trades on the London Stock Exchange. The amount of stock on loan is updated daily, but with a three day reporting lag (before 12 December, 2005 the lag was five days). Over time, the coverage of companies in the database increases through the addition of smaller capitalization stocks so that by the end date for this sample, 31 May, 2007, there is stock lending data for 681 companies. The smallest of these companies have market capitalizations of approximately £25 million (approximately U.S.$40 million), as of 2007. A number of companies cease to exist at some point during the 45 months (979 trading days) studied. This could be as a result of a merger or acquisition, the lapsing of the company into administrative receivership, or a change to private ownership. Such companies are included in the database until the date of their de-listing, to prevent survivorship bias. We make use of all stocks in the database and all trading days in the sample for which stock lending data is available.

The Index Explorers database includes the following daily information for each stock:

- Date
- Name of company

[1] Index Explorers data has also been used by Saffi and Sigurdsson (2007) and Mackenzie and Hendry (2008).

- SEDOL (a unique company identifier code)
- Turnover (defined as the number of shares traded that day)
- Stock Price (defined as the previous day's closing stock price)
- Volume (defined as turnover multiplied by stock price)
- Market Capitalisation (defined as number of shares in issue multiplied by stock price)
- Shares on Loan (defined as the number of shares reported to CREST as being on loan)
- Volume on Loan (defined as shares on loan multiplied by stock price)
- Percentage of Market Capitalization on Loan (defined as the volume of shares on loan divided by the market capitalization)
- Dividend Record Dates (the dates on which the recorded owners of shares on that day become entitled to receive the next dividend payment)
- Stock Utilisation Rate (the percentage of shares available for borrowing that are actually borrowed)
- Weighted Mean Stock Lending Fees (a weighted average of the fees paid by stock borrowers to stock lenders on initiation of the stock loan, measured as a proportion of the value of shares borrowed).

We use Datastream to obtain the following data for all for all FTSE All Share Index constituents from 1 September, 2002 to 31 May, 2007:

- Date
- Name of company
- SEDOL (a unique company identifier code)
- Daily stock returns (defined as the total return for a stock on that date)
- Book value per share (this value is generally updated annually for each U.K. company and is reported to the public via financial statements that are published up to six month in arrears. Datastream then 'backfills' the new book value to the end of the last financial year. To account for the possible delay in reporting book value per share and to avoid look-ahead bias, we shift the 'book value per share series' back by six months for each company, thus reflecting what is 'knowable' to market participants at any time)

- Free float percentage of shares (defined as the percentage of the total number of shares in issue that are available to ordinary investors i.e. that are not held away from the market by government or close family interests).

To facilitate the estimation of abnormal stock returns using an asset pricing model, we collect stock returns data for the year before the start of the Index Explorers database. This ‘formation period’ runs from 1 September, 2002 to 1 September, 2003 and is used to estimate the beta of each stock in the study.

Using each company’s SEDOL code as a unique identifier to reconcile stocks across the two databases, we merge the two databases, and construct a data set including trading and fundamental information for up to 681 stocks involved in stock lending activities on the London Stock Exchange, during the period from 3 September, 2003 to 31 May, 2007. Overall, the dataset is an unbalanced panel of data for between 350 and 681 companies covering 979 trading days with 12 data items per firm day, plus a series of transformations such as the natural logarithms of daily stock returns.

2.2 Stock Lending as a Proxy for Short-Selling

Direct data on short-selling is not publicly available in the U.K. Instead, stock lending data is available, on a daily basis. Stock lending acts as a proxy for short-selling, as the process of short-selling generally requires stock to be borrowed to facilitate settlement of the trade. MacKenzie and Henry (2008) state that: “The use of securities lending data is a fairly new innovation in the literature and only a handful of papers have had access to this type of data, including D’Avolio (2002), Cohen *et al.* (2007) and Saffi and Sigurdsson (2007).” However, there are a number of problems with using stock lending data as a proxy for short-selling.

First, shares do not need to be borrowed to undertake ‘naked’ short-selling (i.e. short-selling where there is no intention of subsequently settling the trade). Naked short-selling for periods of one day or longer is unlikely to be common, however, as it involves failed settlement. ‘Repeat offenders’ would soon become known to the brokers for such trades, who would cease dealing with them.[2] Intra-day short-selling, though, does not require the delivery of stock for settlement at the end of the day, and so would not be revealed by daily stock lending data. Jones (2004) finds that intra-day shorting represents about 5% of daily volume in the early 1930s.

Second, stock lending occurs for a number of reasons other than short-selling. In general, borrowing shares results in the temporary receipt of legal ownership of the securities and so the borrower is entitled to dividends, voting rights, and so forth. Strategies exist to benefit from these arrangements. These include borrowing stock so as to exercise a vote at a firm’s General Meeting. Such a strategy would be illegal in the U.S., but it is merely regarded as unethical in the U.K. To prevent this practice, stock lenders are recommended to recall their shares prior to voting dates (Myners, 2001)[3]. Another strategy involving stock borrowing is ‘dividend tax arbitrage’, a strategy that is feasible when a ‘borrower’ has a tax advantage over the ‘lender’. Christoffersen *et al.* (2002, 2005) demonstrate increases in securities lending around dividend record dates. As a result of these various practices, the dataset can become obfuscated. Christophe *et al.* (2005) discuss the problem of obfuscation in short-interest data arising from the aggregation of short positions from market participants with differing motivations (e.g. market makers, option-market arbitrageurs, traders expecting stock price declines). They provide evidence that some of the component parts that are aggregated in short interest data are negatively correlated with one another. With stock lending data, an even greater number of motivations can exist, including financing purposes and borrowing to exercise voting rights. One of the crucial issues for this study concerns the time around the dividend dates, since dividend tax arbitrage is common in practice. To minimize the risk that stock lending for dividend tax arbitrage is confounded with borrowing to facilitate short-selling, we remove data from three weeks before until three weeks after the dividend record date for each stock in this study of stock lending data. This is consistent with the method employed by Saffi & Sigurdsson (2007). In studies that use stock lending data, but that do not

2 For instance, the Hong Kong Stock Exchange (1998) reported it conducted 768 investigations, and made 15 prosecutions in 1997 for breach of short-selling rules that included a prohibition of ‘naked’ short-selling.
[3] Myners Report, 2001. http://www.hmtreasury.gov.uk/media/DCB/53/myners_principles_web.pdf

adjust for dividend tax arbitrage (e.g. Au *et al.*, 2007), results have not been consistent with those found in the bulk of the literature.

Third, the extent to which market practitioners fail to fulfil their obligations to report stock lending to the market authorities is a further limitation on the use of stock lending data as a proxy for short-selling. Discussions with practitioners involved in stock lending suggest that this problem is rare, but unavoidable.

Finally, derivatives can be used to effect transactions that are economically equivalent to short-selling (Ofek *et al*., 2004). The extent to which the use of derivatives to facilitate short-selling is transmitted into the stock lending market influences the usefulness of stock lending data as a proxy for short-selling. Discussions with stock-lending practitioners suggests that the majority, but not all, short-sale-equivalent trades using derivatives are ultimately hedged by the counter-parties to those trades, through borrowing stock and selling short.

2.3 Advantages and Limitations of the Dataset

A number of studies into short-selling make use of monthly data (Senchack and Starks, 1993 and Dechow *et al.*, 2001, Gamboa-Cavazos and Savor, 2007). However, Christophe *et al.* (2007) criticise the use of monthly short-selling data, as it “represents only a snap-shot of total shorted shares on one day during the month.” Cohen *et al.* (2007) find that almost half the securities lending contracts they study are closed out within two weeks, while the median contract length is 11 days. This suggests that monthly data could be inadequate for understanding the trading practices of short-sellers. The dataset used for this study incorporates daily data on shares borrowed (a proxy for shares shorted). This higher frequency data allows for an appropriate degree of granularity for the study of crowded exits.

Some studies obtain trade-by-trade (or ‘flow’) data on stock lending or short-selling. These same studies tend to investigate shorter time periods. There is a balance to be had, though:

although flow data provides the highest degree of granularity, it would be arduous to study flow data for long periods of time. However, studies over longer periods could reveal trends and cycles not found in shorter periods. Christophe *et al.* (2007) take flow data for a ten month period and aggregate it into daily data. Similarly, Diether *et al.* (2008) obtain tick by tick short-sale data for over 3,800 stocks during 2005 and aggregate it for each stock to the daily level.

Due to differences in regulatory and institutional frameworks, evidence from studies of U.S. data is not necessarily representative of behaviour outside the U.S. markets. For example, in the United Kingdom, the Financial Services Authority does not impose specific restrictions or controls on short-selling, unlike in the U.S. Instead, short-sellers are subject to general market and regulatory arrangements, including market abuse principles. Furthermore, studying data from outside the U.S. can be used to counter the criticism that observed regularities in empirical studies are simply due to data mining. A limited number of studies investigate short-selling and its impact on stock prices outside the U.S.(Aitken *et al.*, 1998, Biais *et al.*, 1999, Poitras, 2002, Ackert and Athanassakos, 2005, and Au *et al.*, 2007). However, these studies do not involve an investigation of crowded exits, as considered in this paper.

Geczy *et al.* (2002) examines shares available for borrowing (and thus available for shorting), based on a single lender of stock for a twelve month period. D'Avolio (2002) examines an eighteen month period of data from one stock lender. This research draws upon a longer time period than either Geczy *et al.* or D'Avolio, and uses market-wide data on stock lending, thus removing the problem of substitution effects across lenders that might be present in studies based upon a single stock lender. As such, this research makes a contribution to the empirical literature.

By observing the differences in returns between equally-weighted and value-weighted portfolios, Asquith *et al.* (2005) demonstrate that the level of short-selling is more informative as a negative sentiment indicator for smaller capitalization stocks than for larger stocks. Au *et al.* (2007) suggest that a study based on larger capitalization stocks will produce more conservative estimates for the relationship between short-selling and stock returns compared to a study that includes smaller, less liquid stocks. The smallest stocks in our dataset have a market capitalization of approximately £25 million. Thus, a limitation of the dataset is that it includes only the larger stocks listed on the London Stock Exchange. However, this also suggests a degree of conservatism in any findings.

2.4 Descriptive Statistics

The dataset forms an ‘unbalanced panel’ dataset in which some cross-sectional units have some of the time periods missing. This form of panel is a result of the number of companies recorded in the Index Explorers database growing over time as smaller capitalization stocks are added. The resulting dataset contains 10,259,946 observations in the overall sample; 6,542,712 of which are non-blank.

In Table 1, descriptive statistics are produced for three points in time: the first day of the sample time period for which all the variables existed (09/01/2003), the last day of the sample time period (05/31/2007) and the mid-point (07/15/2005). The mean percentage of market capitalization on loan is a low figure for each of the snapshot dates (less than 3.5%), but is positively skewed. From the Jarque-Bera probabilities, it can be seen that the first five variables are not normally-distributed.

[INSERT Table 1 ABOUT HERE]

Histograms for each of six variables are presented in Table 2. For the purpose of visualization, the histograms are constructed using the mid-point snapshots. In order to improve the granularity of the histograms, any outliers further than three standard deviations from the mean are removed (this is done only for illustrative purposes with these histograms and does not affect the rest of the study).

[INSERT Table 2 ABOUT HERE]

Tables 3 and 4 present descriptive statistics for the logarithms of the six variables considered earlier.

[INSERT Table 3 ABOUT HERE]

[INSERT Table 4 ABOUT HERE]

An examination of the time series of percentage of market capitalization on loan series for each stock shows that these can be volatile series. Dividend-paying stocks often experience large increases in shares on loan around divided record dates, indicating a dividend capture effect that is consistent with dividend tax arbitrage. Nevertheless, some cross-sections experience a consistently high level through the observed period. During some dates in the sample the maximum value for this series exceeds 100% for some companies, signifying that borrowed shares have been re-lent.

For the first and last snap-shot dates (09/01/2003 and 05/31/2007), we construct box-plots for each of the six variables considered above, to provide a visual summary of outliers in the dataset. These are shown in Table 5.

[INSERT Table 5 ABOUT HERE]

For each variable considered above, we identify outliers in the study sample using two techniques. First, we observe data points that lie more than three standard deviations from the mean for each variable. Secondly, we observe daily changes in each variable that are more than three standard deviations from the mean daily change. Table 6 reports the frequency of these outliers by variable. In studying crowded exits, we are concerned with exceptional situations for short-sellers. As such, 'outliers' in each variable are likely to be important and so are not removed from the dataset.

[INSERT Table 6 ABOUT HERE]

2.5 Asset Pricing Model for Estimating Abnormal Returns

In choosing an asset pricing model for the purposes of calculating abnormal returns, we note that Asquith and Moelbroek (1996) establish that the negative relation between excess returns and short positions is robust to a variety of techniques for calculating excess returns. Dechow *et al.* (2001) measure excess returns by adjusting each firm's return by the equal weighted return for all NYSE and AMEX shares over the same time period. They make no adjustment for risk across firms and cite previous research in this field that has been robust to changes in the asset pricing model used. Figlewski (1981) and Figlewski & Webb (1993) make use of the CAPM model. Asquith *et al.* (2005) and Boehmer *et al.* (2008) use several asset pricing models to estimate abnormal returns for short-sellers but find no significant difference between the results. Cavazos and Savor (2007) apply both benchmark-adjusted returns approach and Fama-French three factors regression to study the relationship between short selling activities and subsequent abnormal returns, and obtain similar results for both. In fact, results in this research space have been *uniformly* robust to changes in asset pricing model. Noting this, we use the CAPM model for its simplicity and its relevance to practitioners. Abnormal returns are calculated as:

$$AR_{i,t} = R_{i,t} - \left[R_{f,t} + \beta_i\left(R_{m,t} - R_{f,t}\right)\right] \qquad (1)$$

Where $R_{i,t}$ is the return of stock *i* on day *t*, and $R_{f,t}$ is the risk-free rate on day *t*. $R_{m,t}$ is the market return on day *t*, which is calculated from the total return index for the FTSE All Share index, a broad, capitalization weighted index for the London market. β_i represents the correlation between the returns on stock *i* and the market return premium, which is estimated using CAPM over the period from 2 September, 2002 to 31 August, 2003, which is a one-year period that precedes my stock lending sample data period. We use 3-month LIBOR as the risk free rate. LIBOR is commonly used as a risk-free proxy. We note that this series was 'well-behaved' during the period of study, but later became unusually dislocated during the 2007-2009 U.S. and U.K. banking crisis. In a study that uses U.K. stock lending data from CREST, Au *et al.* (2007) use weekly one-month LIBOR rates as their measure of the risk-free rate and estimate one-month cumulative abnormal returns relative to FTSE 350 index returns.

3. Methodology

3.1 Definitions of Variables

We might expect firms with more shares in issue to have a potentially greater amount of shorted stock. Thus, we standardize shares on loan first by the number of shares outstanding and, second, by the free float number of shares. Each of these measures serves as a proxy for short interest.

The proportion of market capitalization on loan (MCOL) of a stock on any given day is calculated as:

$$MCOL_{i,t} = \frac{\text{Shares on loan}_{\text{i,t}}}{\text{Outstanding Shares}_{\text{i,t}}} \qquad (2)$$

This measure represents the proportion of a company *i*'s outstanding shares that are on loan on day *t*. By dividing by outstanding shares, this ensures that the measure of short interest is not dominated by larger firms.

We introduce the proportion of free float on loan (FFOL) as a second measure of short-interest that is better attuned to the liquidity of a stock. It is calculated as:

$$FFOL_{i,t} = \frac{\text{Shares on Loan}_{\text{i,t}}}{\text{Size of Free Float}_{\text{i,t}}} \tag{3}$$

The 'size of free float' is the total number of shares in issue that are available to ordinary investors (i.e. excluding shares held by government or long-term family interests).

To identify 'crowded positions', we also measure the shares on loan for each firm day relative to the average daily number of shares traded in the company[4]. This measure is widely used by short-sellers and is known as the Days to Cover Ratio (DCR). The higher this ratio, the more difficult it should be for short-sellers to liquidate their positions without having market impact. The ratio is calculated as:

$$\text{Days to Cover Ratio}_{\text{i,t}}\ (\text{DCR}) = \frac{\text{Shares on Loan}_{\text{i,t}}}{\text{Average Daily Shares Traded}_{\text{i,t}}} \tag{4}$$

$\text{Shares on Loan}_{\text{i,t}}$ is the closing number of shares on loan for stock *i* on day *t*.

$\text{Average Daily SharesTraded}_{\text{i,t}}$ is the moving average of the number of shares traded for stock *i* from days (*t*-61) to (*t*-1). We choose 60 days of trading volume as a compromise between

[4] The average daily number of shares traded in a company is also known as 'normal market size'.

the risk of including out-dated information on number of shares traded and the risk of one or more exceptional days influencing the moving average figure.

3.2 Constructing Portfolios

One aim of this paper is to measure the abnormal returns of stocks experiencing crowded exits. A portfolio approach is applied as it allows us to replicate gross and risk-adjusted returns for a potential trading strategy; and it captures certain non-linearities that might characterize the patterns of subsequent returns (Pan and Poteshman, 2006). For each day, we sort the data to construct equal-weighted portfolios containing stocks identified as going through crowded exits. We study the characteristics of the securities included in the crowded exit portfolios, and estimate the abnormal portfolio returns for subsequent time periods.

We use two steps to select portfolios of stocks. The first step is a simple sort, identifying stocks on each day based on their Days to Cover Ratio (DCR) ranking relative to other stocks. This simple sort thus creates portfolios that differ by the 'crowdedness of short positions'. The second step is a double sort. In addition to sorting by DCR, we also divide portfolios according to whether or not each stock is experiencing exceptional short covering.

Simple Sorts

For each day, we rank all stocks by DCR. We then construct three portfolios containing the 99^{th}, 95^{th}, and 90^{th} percentile of stocks by DCR. These higher percentiles represent the most crowded short positions under our definition. A prerequisite for a crowded exit is that the stock should have a high level of short interest relative to its liquidity, and this simple sort captures that condition.

Double Sorts

We carry out simultaneous sorts, creating portfolios based on a ranking of stocks by DCR and also whether or not they meet the test of showing an exceptional decrease in shares on loan. Instead of sorting stocks into independent quintiles twice, we sort stocks into 99th, 95th, and 90th percentiles based on DCR, and narrow down the portfolios by controlling for exceptional changes in short interest on the previous day. We define the resultant portfolios as portfolios of stocks experiencing crowded exits: these portfolios include stocks with high DCRs, and showing exceptional changes in short interest on the previous day. We use two criteria to define an exceptional reduction in the short interest level. First, we filter the data to include only stocks with decreasing shares on loan. See equation (5) below:

Change in shares on loan (*t*) = shares on loan (*t*) – shares on loan (*t-1*) (5)

A negative number indicates that short-sellers are covering their positions on day *t*.

Only publicly-traded stocks are generally loaned and so it important in any study of liquidity problems to consider each firm's free-float rather than total shares outstanding. We use the proportion of free float on loan in defining an exceptional decrease in the short interest level. We first calculate the change in the free float on loan (CFFL) from day *t-1* to day *t*. The average change across all stocks for day *t* is defined as the cross sectional mean on day *t*, according to the equation below:

$$\text{Average market change } (CFFL_{m,t}) = \frac{\sum_{i=1}^{n} CFFL_{i,t}}{n} \qquad (6)$$

Where *n* is the total number of stocks in the universe on day *t*. We adjust the daily change in free float on loan for stock *i* ($CFFL_{i,t}$) for the market average change, and obtain the adjusted daily change in free float on loan relative to the market average change, as shown below:

$$\text{Relative daily change for stock } i \; (RCFFL_{i,t}) = \frac{CFFL_{i,t}}{CFFL_{m,t}} \tag{7}$$

Next, we test whether or not each $RCFFL_{i,t}$ is exceptional. For each firm day, we calculate $RCFFL_{i,t}$ for each day from day (*t-21*) to day (*t-1*) and measure the mean and standard deviation of this series. If $RCFFL_{i,t}$ exceeds ± 2 standard deviations, we determine this to be an exceptional change. If this exceptional change is accompanied by fewer shares on loan and a lower CFFL, it is defined as an exceptional decrease in the level of short interest. Using this technique and having already undertaken a simple sort, we proceed to separate each of the DCR groups into two smaller portfolios: a Crowded Exit Portfolio (where each stock experiences an exceptional decrease in short interest) and a Not Crowded Exit Portfolio (the stocks do not experience an exceptional decrease in short interest).

We study the characteristics of securities found in the Crowded Exit Portfolios and compare to those for the Not Crowded Exit Portfolios. These characteristics include the short interest ratios defined in Section 3.1; and liquidity factors (turnover by shares, and the percentage of outstanding shares that are free floating). We also measure fundamental factors, including market capitalization, market-to-book, volatility of returns, and past returns. The 'past return' is the raw return for a portfolio of stocks over the previous 20 trading days.

3.3 Abnormal Returns around Crowded Exits

Portfolio abnormal returns are estimated from the CAPM model, as described in Section 2.5. We calculate equal-weighted portfolio abnormal returns for each portfolio resulting from a sort. In measuring abnormal returns following crowded exits, for each portfolio we skip one day and hold the portfolios over *N* trading days. We start the holding period on day (*t+2*) to reduce the risk that stock prices are disproportionately at either bid or ask (the 'bid-ask bounce problem'). We calculate Cumulative Abnormal Returns (CAR) over a series of holding periods (1, 5, 10, 20 and 60 days) to investigate the aggregate losses to short-sellers who cannot or do not cover their positions.

Cumulative abnormal returns for periods of up to 60 days are estimated for each day, and thus there is a problem of 'overlapping' data to address. Estimates based on overlapping periods could capture autocorrelation and heteroskedasticity in a firm's excess returns, thus biasing the results. Senchack and Starks (1993) use monthly data and apply an event window covering 15 days before and after short interest announcement date to avoid the overlapping problem. Angel et al. (2003) study stocks returns by partitioning their study sample into non-overlapping four-day sub-samples. However, we wish to use our daily data to study periods of up to 60 days and so partitioning would not be suitable for this study. Since we rank by DCR daily and hold portfolios for a subsequent *N* days, we need to adjust for unknown autocorrelation and heteroskedasticity in returns. The Newey-West (1987) Heterockedasticity Autocorrelation Covariance (HAC) Matrix Estimator is widely used for such adjustment. Diether *et al.* (2008) sort stocks into quintiles based on the percentage of daily trading volume due to short selling, and study the day ($t+2$) to day ($t+5$) holding period. They use the Newey-West (1987) approach with lag 5 to adjust for autocorrelation over the overlapping holding period. However, Petersen (2006) notes that, although the Newey-West HAC matrix estimator is more efficient, its weighting scheme is not as optimal as clustered White (1980) standard errors. Also, if there is a requirement to adjust for autocorrelation, the test is mis-specified. To solve this problem whilst making full use of the daily data, we undertake a calendar-time approach to calculate average daily returns. This approach is used by Mitchell and Stafford (2000) and Boehmer *et al.* (2008) to address the overlap problem.

The daily abnormal return on portfolio *p*, $AR_{p,t}$, is given by:

$$AR_{p,t} = \frac{1}{I}\sum_{i=1}^{I} AR_{i,t} \tag{8}$$

$AR_{i,t}$ is the abnormal return for the i^{th} stock assigned to portfolio p based on the daily ranking of DCR. I is the number of stocks contained in the portfolio.

We skip one day to avoid the bid-ask bounce problem and estimate the abnormal return from day (*t+2*). We establish the window for one day [*t+2*, *t+3*], 5 days [*t+2*, *t+6*], 10 days [*t+2*, *t+11*], 20 days [*t+2*, *t+21*], and 60 days [*t+2*, *t+61*]. The Cumulative Abnormal Return (CAR) is estimated based on the above windows.

4. Results

Table 7 shows summary statistics for the entire sample period (1st September 2003-31st May 2007) and for three 'snapshots': the sample beginning date (1st September), the sample mid-date (15th July 2005), and the sample end date (31st May 2007). Panel A presents statistics for variables related to stock lending. Panel B presents statistics for stock characteristics. In Panel A, by comparing the mean to the median and the upper percentiles for shares on loan, it is clear that the distribution of shares on loan is skewed. Likewise, the distribution of the Days to Cover Ratio (DCR) is also skewed. Whereas Cavazos and Savor (2007) find increasing short interest for NASDAQ stocks between 1988 and 2001, there is no obvious increasing trend in short interest for London Stock Exchange stocks during the period 2003 to 2007.

[INSERT Table 7 HERE]

4.1 Simple Sorts

For each day, stocks are ranked according to DCR and portfolios containing the 99th, 95th and 90th percentile of stocks by DCR are constructed. The portfolio characteristics resulting from these simple sorts are shown in Table 8:

[INSERT Table 8 HERE]

Panel A reports the variables related to short interest and reveals that the higher DCR percentiles have higher short-interest. Panel B presents statistics associated with liquidity factors: liquidity is generally poorer in portfolios with higher DCRs. Thus, high DCRs typically result from the *combination* of high short interest and poor liquidity. Panel C presents statistics for other portfolio characteristics, including stock return volatility, market capitalization, book-to-market ratio and past returns. There is no apparent relationship between volatility and DCR. The higher DCR portfolios exhibit greater median, but lower mean, market capitalizations in comparison to the whole sample. The higher DCR portfolios exhibit median book to market ratios that are similar to that of the whole sample, although the mean book-to-market ratios are greater, suggesting skew in the distribution of this ratio. Boehmer *et al.* (2008) point out that although short-sellers are able to identify over-valued stocks, high levels of short-selling are neither necessarily nor sufficiently related to a low book-to-market ratio. There is also no apparent relationship between past returns and DCR.[5]

Table 9 presents the abnormal returns and cumulative abnormal returns associated with higher DCR portfolios.

[INSERT Table 9 HERE]

Table 9 reveals positive abnormal returns for each of the higher DCR portfolios over each time period considered. Statistical significance is generally stronger over the longer holding periods; and for the 90th and 95th percentiles compared to the 99th percentile. This latter effect

[5] In further work that is not reported here, we find that that there is a statistically significant (albeit economically modest) evidence of under-performance by stocks with the highest levels of short-interest compared to stocks with the lowest levels of short-interest, once adjustment has been made for dividend capture. This is consistent with the literature on short-selling and stock returns.

is due to the lower volatility of abnormal returns in the 90^{th} and 95^{th} percentile portfolios, such that statistical significance can be established at a lower abnormal return.

4.2 Double Sorts

Table 10 shows portfolio characteristics for the higher percentile DCR portfolios, separated into ‘crowded exit’ portfolios and ‘all’ portfolios. This allows for a comparison between the characteristics of stocks experiencing crowded exits, and all stocks that belong to higher percentile DCR portfolios.

[INSERT Table 10 HERE]

In Panel B, it can be seen that mean and median turnover by shares is dramatically lower for the ‘Crowded Exits’ portfolios compared to the ‘All’ portfolio, suggesting that lower liquidity is an important factor in explaining crowded exits. Panel C reveals little difference in volatility of returns, firm size or past returns between the ‘Crowded Exits’ portfolios and the ‘All’ portfolios. However, the Book-to-Market ratio appears lower for each of the ‘Crowded Exits’ portfolios than for the ‘All’ portfolios (i.e. there is a suggestion that crowded exits are more commonly associated with non-value or ‘glamour’ stocks).

We examine each of the stocks appearing in the ‘Crowded Exits’ portfolios to identify if there are Regulatory News Service releases around the time of the crowded exit. In approximately half the cases, there are regulatory news announcements in the period from 7 days before the start of exceptional short covering. This suggests that publicly-released, company-specific news could be the catalyst for a crowded exit in some, but not all, cases. Stocks typically stay in the crowded exit portfolio for a limited number of days (a mean of 3.35 days for the 99^{th} percentile portfolios, 3.55 days for the 95^{th} percentile portfolios and 4.45 days for the 90th percentile portfolios).

For the crowded exit portfolios, we calculate equal-weighted portfolio returns using the calendar-time approach over holding periods of 1, 5, 10, 20, and 60 trading days. As before, we skip one day to counter the bid-ask bounce problem. This approach is repeated every day. We expect stocks experiencing crowded exits to show higher positive AR and CARs than stocks that do not experience crowded exits. Results are shown in Table 11:

[INSERT Table 11 HERE]

For each percentile, the 'Crowded Exits' column reports the AR and CARs for portfolios of stocks that have high Days to Cover Ratios but that also show exceptional decreases in short interest – each of these stocks is said to experience a 'crowded exit'. The 'Difference' column shows the difference between stocks experiencing crowded exits and those that do not, within each percentile group. 'Crowded Exit' portfolios have positive AR and CARs, most of which are statistically significant. Comparing to the simple sorts, these AR and CARs are also all higher. For example, the highest CAR is observed in the 99th percentile over the holding period of 60 trading days, with 18.93%, which is statistically significant at the 5% level, while the CAR(+60) for the 99th percentile based on a simple sort is only 2.03%, significant at the 10% level. The mean CAR(+60) for the 99th percentile Crowded Exit portfolios, at 18.93%, is also economically significant. This indicates potentially large losses for short-sellers during crowded exits. Noting from Table 10 that the 99th percentile has an average DCR of over 147 days, it is unsurprising that such stocks could remain crowded after 60 days. Although the positive CARs are not statistically significant over shorter periods, they are all statistically significant over periods of 10 days or greater.

The results are consistent with the hypothesis that crowded exits represent a risk to short-sellers. For longer holding periods, results are both statistically and economically significant. The greatest CARs are in the highest DCR portfolios.

As a robustness check, we consider stocks that have high Days to Cover Ratios and that also exhibit a decrease in shares on loan over a 5 day period (as opposed to exhibiting an ‘exceptional’ decrease in shares on loan as defined in Section 3.2). We find that the abnormal returns for each category are generally no longer positive, and that none is statistically significantly different from 0. This reveals that it is the ‘exceptional’ nature of short-covering associated with crowded exits that leads to losses for short-sellers.

4.3 Adjustment for Arbitrage

Not all short-sales are motivated by negative opinions on a stock. For example, short-sellers might short stocks to conduct convertible bond arbitrage and so take advantage of relative mispricing between a stock and a convertible bond issued by the same company. Where a short-seller is arbitrage-motivated, he will be partially hedged against movements in the stock price. The presence of such arbitrageurs could thus obfuscate our results and weaken the power of the tests. We use Thomson One Banker to identify firms with convertible bonds as part of their capital structure. We then re-estimate abnormal returns and CARs for the Double Sorts, separating firms with convertible bonds from those without. Cavazos and Savor (2007) separate firms with convertible securities outstanding in excess of $10M, from those firms below this threshold. In this study, we separate firms with any convertible bonds in issue from those without convertible bonds, to completely remove any obfuscation due to convertible bond arbitrage. Approximately one fifth of stocks in the panel have convertibles within their capital structure. Table 12 shows the results from our double sorts, adjusted for arbitrage-motivated short-selling.

[INSERT Table 12 HERE]

We expect greater CARs for the non-convertible portfolios compared to the convertible portfolios, as short positions in the non-convertible portfolios are not hedged by long positions in convertible bonds. In all cases we find greater ARs and CARs for the non-convertible portfolios, as expected. For the arbitrage-motivated ‘Convertible’ portfolios, all but one of the AR and CARs are insignificant at any level. This is consistent with the findings of Diether *et al.* (2008) and Cavazos and Savor (2007) on arbitrage-motivated short-selling.

5. Conclusions

Crowded exits represent an indirect constraint on short-selling. They have yet to be examined in the literature, and this study fills this gap. Crowded exits arise in stocks where short-sellers hold large positions relative to normal trading volume, and when a catalysts prompts short-sellers to cover their positions rapidly and simultaneously. A variety of catalysts are possible, including, but not limited to, public news releases by companies. Stocks experiencing crowded exits are generally associated with higher short interest and poorer liquidity. Those short-sellers who successfully cover their positions early avoid losses, indicating that they are well-informed. However, crowded exists are associated with economically and statistically significant losses to those short-sellers who do not cover their positions. As such, the risk of a crowded exit represents an indirect constraint on short-selling.

It is rational for investors to take account of published evidence on stock market anomalies. Indeed, a number of quantitative analysts incorporate empirical evidence on stock market anomalies into their investment processes, in their constant search for out-performance. Various studies suggest that the publication of empirical research influences investor behaviour. For example, Lev and Nissim (2004) study short-selling and the 'accruals anomaly' and find that in recent years institutions have altered their portfolio positions more actively in response to accrual disclosures. Wu (2008) argues that "short sellers appear to exploit the [post earnings announcement] drift by increasing (decreasing) shorting immediately following negative (positive) earnings surprises." There exists a substantial body of literature showing that heavily shorted stocks perform poorly. Furthermore, Cohen *et al.* (2007) show that increasing borrowing demand for a stock is followed by poor performance. These studies suggest a potential trading strategy for short-sellers: identify heavily shorted stocks (or stocks with increasing borrowing demand) and build short positions in those stocks. However, imitation strategies such as these change the market dynamics and can lead to unexpected consequences (see Surowiecki, 2004). With imitation, short-positions become more crowded, and the risk of 'crowded exits' increases. This could lead to examples of 'counter-performativity', as described by MacKenzie (2006), whereby the widespread and plentiful practice of short-selling, as assumed in economic models such as Arbitrage Pricing Theory, leads not necessarily to a more efficient market, but to an increasing number of occasions on which stock prices move temporarily away from fair value. Indeed, Irvine (2005) finds that stocks with higher short interest in any given month also have greater return skewness the next month. The *path of stock returns* can be important to investors employing leverage (who are liable to margin calls or subject to loan covenants) and to investment agents using open-ended fund structures (who are subject to the risk of redemption by clients). Even temporary market imbalances can lead to unexpected, *permanent* losses as these classes of investor become unable to hold on to losing positions. Crowded exits can thus create path dependency problems for short-sellers.

This research makes a contribution to the literature by furthering our knowledge of indirect short-sale constraints. It also makes a practical contribution, as our findings suggest practical steps that short-sellers can take to mitigate crowded exit risk. First, short-sellers should be risk-aware when short-selling less liquid stocks with high days-to-cover ratios. Secondly, given the prolonged nature of crowded exits, short-sellers should cover their positions immediately upon observing exceptional levels of covering by other shorts-sellers in crowded positions. However, such short-covering will in itself exacerbate the crowded exit effect for others. A further difficulty in this process is that data on stock lending and short-selling is often publicly available only with a time lag. Under such circumstances, private data on stock lending flows and short-covering can become valuable.

Table 1: Descriptive Statistics for the Raw Dataset

Descriptive statistics are provided for three points in time: the first day of the sample time period (01/09/2003), the mid-point (15/07/2005) of the sample time period and the final day of the sample time period (31/05/2007). The descriptive statistics are parameters that measure central tendency, dispersion, minimum/maximum values, number of observations, skewness, kurtosis and Jarque-Bera statistics for stock price, market capitalization, percentage of market capitalization on loan, shares on loan, book value per share* and free float number of shares (%).

		Price (GBp)	Market Cap (mill GBP)	Market Cap on Loan (%)	Shares on Loan (mill)	Book Value per Share (GBP)	Free float number of shares (%)
01/09/2003	Mean	348.9678	2190.933	2.426836	28.13055	1.523835	56.71614
	Median	217.75	311	1.62	5.5	1.1105	57
	Maximum	20500	95755	15.63	1078.8	186.318	100
	Minimum	2.35	47	0.15	0.1	-422.447	9
	Std. Dev.	985.9779	8613.22	2.50429	79.08176	18.8214	17.15801
	Skewness	16.55132	8.035531	2.482568	9.250658	-16.40918	-0.182926
	Kurtosis	317.4105	75.15189	10.31674	116.0577	421.1521	2.843907
	Jarque-Bera	2440439	112015.6	895.895	150383.2	4662099	3.757554
	Probability	0.00	0.00	0.00	0.00	0.00	0.152777
	Observations	586	492	275	275	636	570
15/07/2005	Mean	423.317	2503.904	3.48463	32.44019	2.511012	78.57348
	Median	266	381	2.35	8.5	1.261	82
	Maximum	23650	130630	19.32	866.1	221.26	100
	Minimum	5.85	51	0.32	0.2	-76.755	11
	Std. Dev.	1030.296	9924.584	3.137033	75.87327	10.13917	17.03667
	Skewness	18.55561	8.7192	1.647085	6.389255	15.77574	-0.921704
	Kurtosis	409.2458	91.73508	5.882677	57.78028	348.8487	3.510788
	Jarque-Bera	4416875	184346	248.2996	41002.37	3256384	95.44044
	Probability	0.00	0.00	0.00	0.00	0.00	0.00
	Observations	637	541	311	311	648	626
31/05/2007	Mean	610.4427	3034.235	3.037874	25.2274	3.314581	74.67109
	Median	399	463	1.78	3.00	1.467	77
	Maximum	26725.01	109377	29.33	3793.2	264.7	100
	Minimum	5.85	20	0.01	0.00	-2.855	18
	Std. Dev.	1203.783	10065.52	3.60918	154.0299	13.12218	17.355
	Skewness	15.83103	6.728114	2.623158	22.11777	17.33452	-0.648486
	Kurtosis	330.5056	57.06653	12.92178	538.0428	337.5389	2.958836
	Jarque-Bera	3071946	82650.91	3506.041	8022336	2229372	47.56819
	Probability	0.00	0.00	0.00	0.00	0.00	0.00
	Observations	681	639	668	668	473	678

** For the BV variable the snapshots presented are for the BV shifted.*

Table 2: Histograms for the Raw Dataset

Histograms for six variables (stock price, market capitalization, percentage of market capitalization on loan, shares on loan, book value per share and free float number of shares (%)) are constructed. For the purpose of visualization the histograms are produced using the mid-date snapshot (15th July, 2005). In order to improve the granularity of the histograms, outliers of greater than three standard deviations from the mean are removed (this is done for the illustrative purposes only).

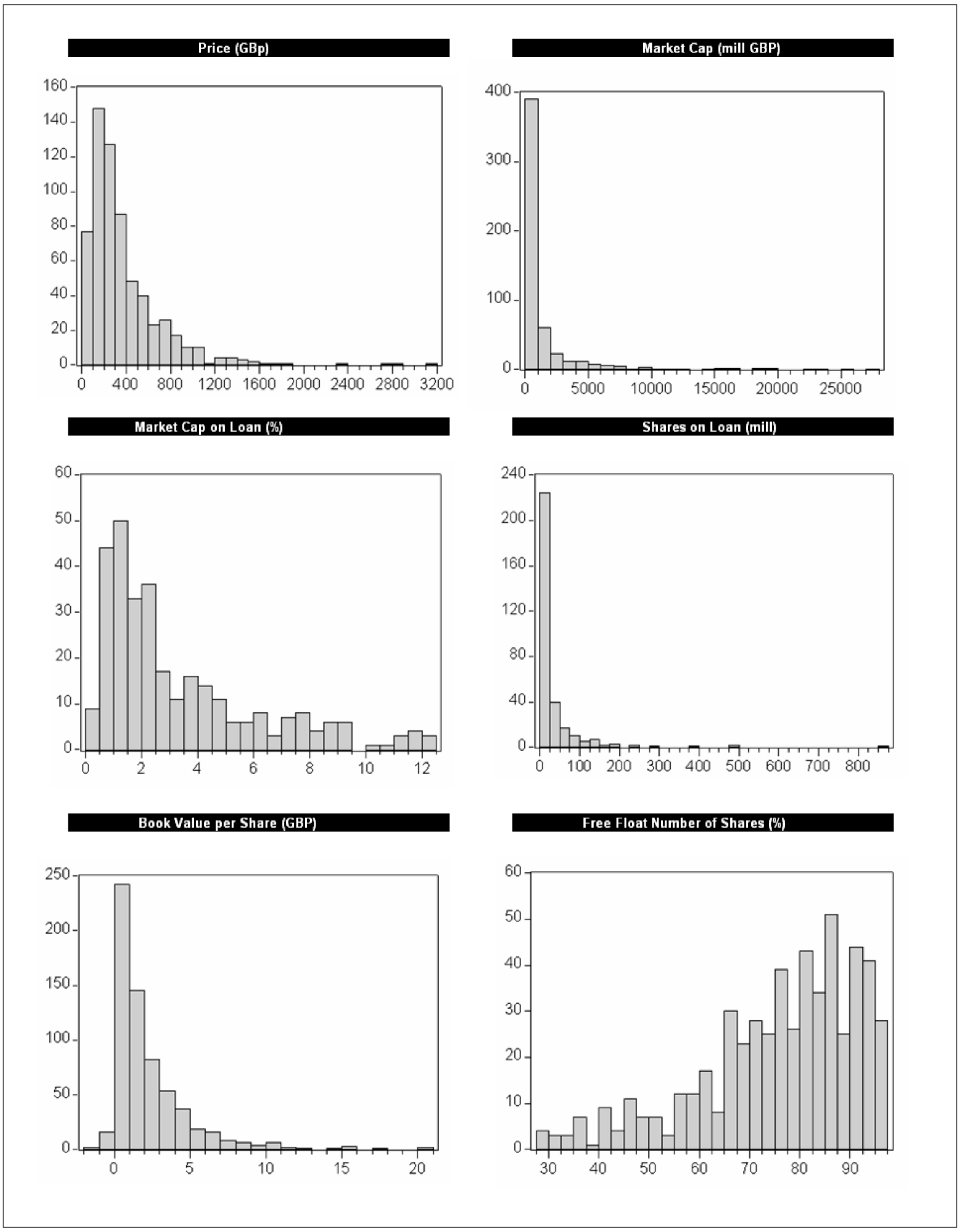

Table 3: Descriptive Statistics for the Logarithmic Dataset

Descriptive statistics are provided for three points in time: the first day of the sample time period (01/09/2003), the mid-point (15/07/2005) of the sample time period and the final day of the sample time period (31/05/2007). The descriptive statistics are parameters that measure central tendency, dispersion, minimum/maximum values, number of observations, skewness, kurtosis and Jarque-Bera statistics for six variables: stock price, market capitalization, percentage of market capitalization on loan, shares on loan, book value per share* and free float number of shares (%).

		Price (GBp)	*Market Cap (mill GBP)*	*Market Cap on Loan (%)*	*Shares on Loan (mill)*	*Book Value per Share (GBP)*	*Free float number of shares (%)*
01/09/2003	***Mean***	5.316258	6.046764	0.487787	1.834715	0.058888	3.981826
	Median	5.383342	5.739793	0.482426	1.704748	0.188966	4.043051
	Maximum	9.92818	11.46955	2.749192	6.983604	5.227455	4.60517
	Minimum	0.854415	3.850147	-1.89712	-2.302585	-5.521461	2.197225
	Std. Dev.	0.968889	1.50577	0.894732	1.773594	1.258237	0.359823
	Skewness	-0.272131	0.993897	0.055387	0.180727	-0.629466	-1.253193
	Kurtosis	5.221265	3.76551	2.824535	2.377743	5.023834	5.077885
	Jarque-Bera	127.7051	93.01533	0.493385	5.93E+00	142.2571	251.7399
	Probability	0.00	0.00	0.78	0.05	0.00	0.00
	Observations	586	492	275	275	601	570
15/07/2005	***Mean***	5.567265	6.24073	0.880144	2.194331	0.252293	4.333748
	Median	5.583496	5.9428	0.854415	2.140066	0.293037	4.406719
	Maximum	10.07112	11.78012	2.961141	6.764	5.399338	4.60517
	Minimum	1.766442	3.931826	-1.139434	-1.609438	-4.710531	2.397895
	Std. Dev.	0.930843	1.460353	0.873153	1.655141	1.204421	0.266321
	Skewness	-0.215372	1.047292	0.055395	0.071518	-0.387375	-1.963846
	Kurtosis	4.853598	3.923735	2.261525	2.446984	4.299419	9.156942
	Jarque-Bera	96.11709	118.1313	7.225814	4.23E+00	59.12548	1391.147
	Probability	0.00	0.00	0.03	0.12	0.00	0.00
	Observations	637	541	311	311	620	626
31/05/2007	***Mean***	5.899454	6.474853	0.415943	1.239666	0.420813	4.279769
	Median	5.988961	6.137727	0.576613	1.193923	0.439221	4.343805
	Maximum	10.19336	11.60256	3.378611	8.240965	5.578597	4.60517
	Minimum	1.766442	2.995732	-4.60517	-2.302585	-3.963316	2.890372
	Std. Dev.	1.01162	1.495919	1.345159	2.045757	1.20275	0.275389
	Skewness	-0.276713	0.932306	-0.619932	0.144035	-0.147303	-1.485895
	Kurtosis	4.001597	3.59038	3.190487	2.387284	4.254811	5.865685
	Jarque-Bera	37.15639	101.8494	43.7971	1.22E+01	31.15017	481.4841
	Probability	0.00	0.00	0.00	0.00	0.00	0.00
	Observations	681	639	668	638	450	678

** For the BV variable the snapshots presented are for the BV shifted.*

Table 4: Histograms for the Logarithmic Dataset

Histograms for six variables (stock price, market capitalization, percentage of market capitalization on loan, shares on loan, book value per share and free float number of shares (%)) are constructed. For the purpose of visualization the histograms are produced using the mid-date snapshot (15th July, 2005). In order to improve the granularity of the histograms, outliers of greater than three standard deviations from the mean are removed (this is done for the illustrative purposes only).

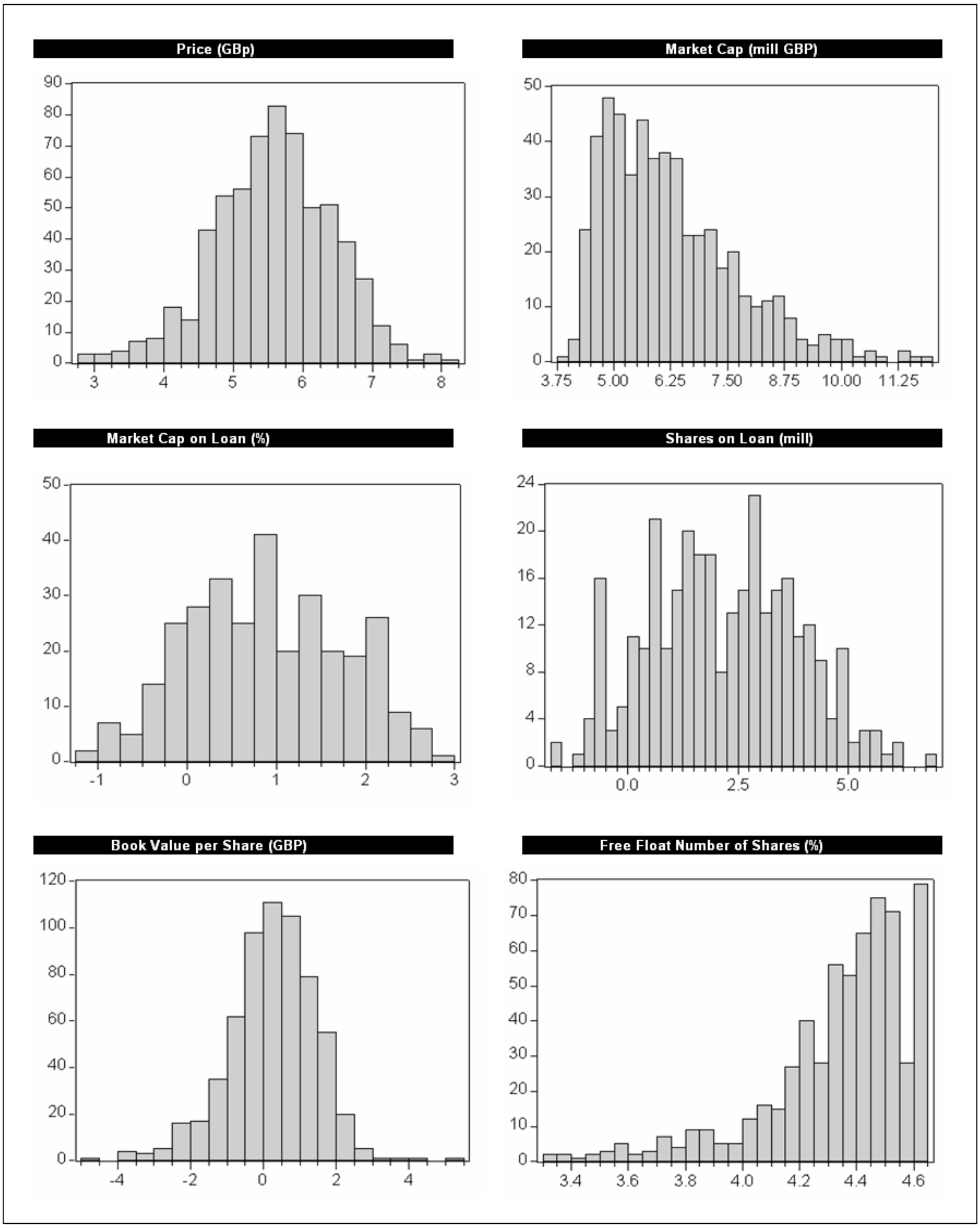

Table 5: Box-plots

Box-plots are constructed for each of the six variables in the dataset for the first (01/09/2003) and for the last (31/05/2007) snap-shot dates. They intend to provide a visual summary of the outliers in the dataset. For most of the variables there are more outliers in the last snapshot of data than in the first one, which is consistent with the notion of a growing panel.

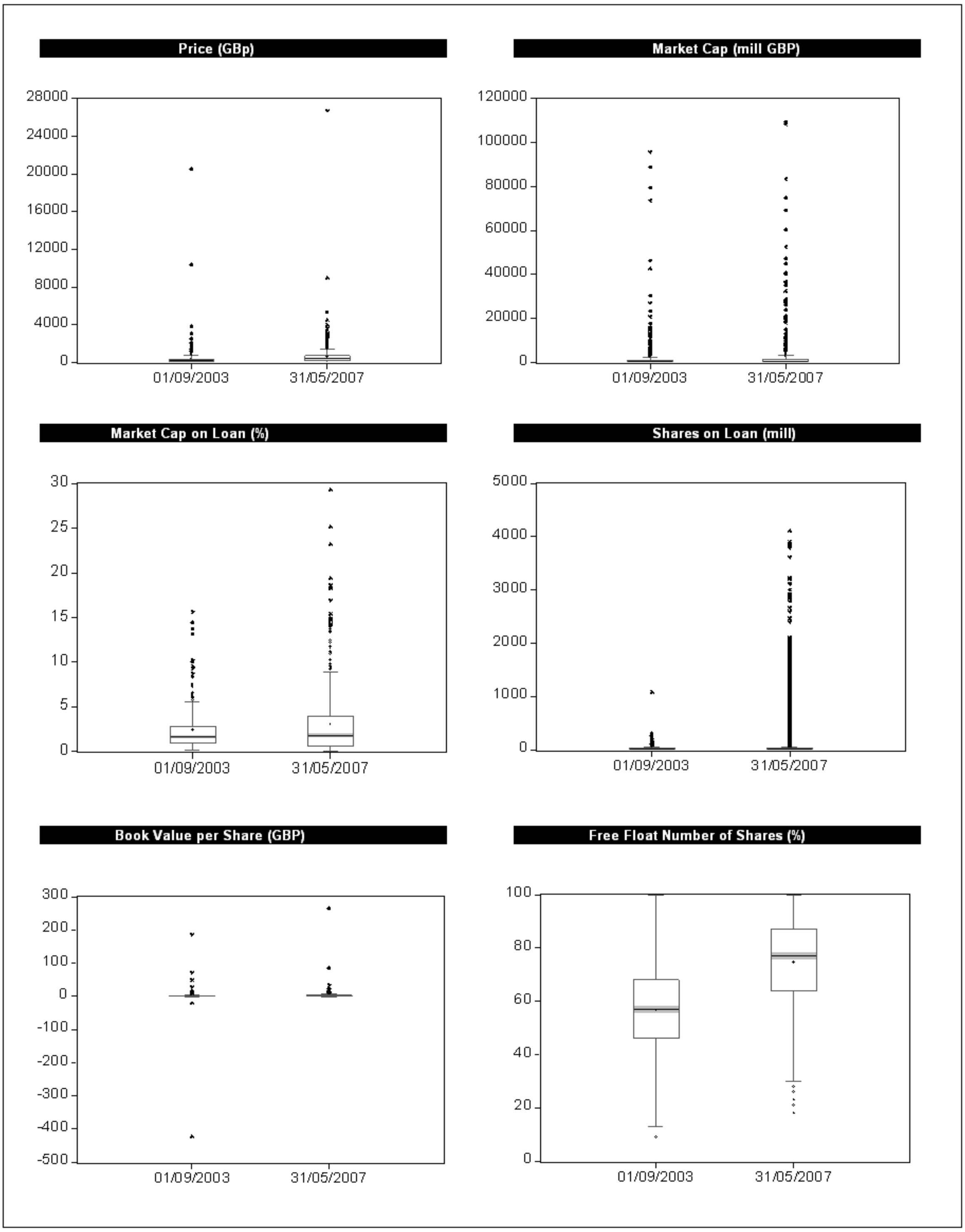

Table 6: Outliers

The top panel of the table shows for each of the six variables the number of observations greater than three standard deviations from the mean as well as its equivalent presented as a percentage of the total number of observations. The bottom panel of the table presents the number of occasions (and its percentage equivalent) each variable has changed in one day by more than three standard deviations from the mean daily change. Both measures aim to capture 'exceptional' data points.

		Price (GBp)	Market Cap (mill GBP)	Market Cap on Loan (%)	Shares on Loan (mill)	Book Value per Share (GBP)	Free float number of shares (%)
> or < than	Number of observations	3443	942	3469	3849	21496	1300
($\mu \pm 3\sigma$)	% of sample	0.3386%	0.17%	0.83%	0.9150%	2.2378%	0.1608%
> or < than	Number of observations	810	1167	3834	6929	NA*	8207
($i_{-1} \pm 3\sigma$)	% of sample	0.0797%	0.21%	0.92%	1.6472%	NA*	1.0151%

*the information is not applicable as BV changes once a year

Table 7: Summary Statistics

Pane A report summary statistics fo different short sellin measures. Shares on Loan is the numbe of shares borrowed over t (0 Sep 2003 to 31 Ma 2007) whic we us a the prox of numbe of shares shorted. Market Cap on Loan is the numbe of s loa divided b market ca over the sampl period. Free Float on Loan is the numbe of shares on loa divided b the size of f whic indicate the relationship short sellin activities and stock liquidity. DC (Days to Ratio is the numbe of shares divided b average daily trading volume whic indicate how lon i takes short sellers to cove their short positions. Pane B s summary statistics of stock characteristics Market Cap is use to measure the size of firm, and B/M refer to lagged boo to r defined i Fam Frenc (1993). Tradin Volum is the numbe of shares trade i the market pe day Free Float show the perce outstandin shares whic are closely held Eac pane report statistics fo the entire sampl period and also snapsho beginning date (01 Sep 2003), the middle date (15 Jul 2005), and the final date (31 May

Panel A: Short Selling Summary

		Shares on loan (millions)	Market Cap on loan (%)	Free float on loan	DCR
01 Sep 2003-31 May 2007	mean	23.39	2.90	4.68	7
	median	4.40	1.84	2.70	4
	Std.Dev	74.99	3.07	5.68	29
01 Sep 2003 (Snapshot 1)	mean	28.84	2.43	4.57	6
	median	5.50	1.64	2.79	3
	Std.Dev	81.60	2.43	5.18	19
15 Jul 2005 (Snapshot	mean	33.38	3.55	4.55	7
	median	9.90	2.41	2.69	5
	Std.Dev	77.58	3.18	4.39	15
31 May 2007 (Snapshot 3)	mean	33.27	3.37	4.42	8
	median	4.35	2.18	2.53	4
	Std.Dev	191.39	3.66	5.49	28

Panel B: Stock Characteristics Summary Statistics

		Market Cap (millions)	Daily Trading Volume	B/M	Free F
01 Sep 2003-31 May 2007	mean	2293.70	3.24	0.67	66
	median	370.00	0.31	0.50	69
	Std.Dev	8485.05	15.74	1.51	21
01 Sep 2003 (Snapshot 1)	mean	1571.23	4.95	0.89	56
	median	272.00	1.19	0.65	57
	Std.Dev	7165.67	11.56	3.36	14
15 Jul 2005 (Snapshot	mean	2495.48	6.14	0.69	82
	median	383.50	1.75	0.53	85
	Std.Dev	10011.37	12.76	1.19	15
31 May 2007 (Snapshot 3)	mean	2700.54	4.71	0.48	74
	median	459.50	0.84	0.36	78
	Std.Dev	7817.87	10.96	0.37	17

Table 8: Portfolios based on Simple Sorts

This table reports the characteristics of portfolios sorted daily by Days to Cover Ratio (DCR) over the period 01 September 2003 to 31 May 2007. DCR is calculated as shares on loan divided by average daily trading volume. The first column shows variables for the entire sample, the following three columns show the 99th, 95th, and 90th percentiles by DCR respectively. Past Return is calculated as the raw percentage return of each portfolio over the previous 20 trading days.

		All	99th Percentile DCR>19.4	95th Percentile DCR>12.4	90th Percentile DCR>8.11
Panel A. Short Interest					
DCR (days)	Mean	7.88	147.26	52.87	34.71
	Median	4.48	62.68	25.76	19.36
	Std. Dev.	29.29	224.63	119.21	86.97
Shares on Loan (in millions)	Mean	23.39	25.90	26.31	33.17
	Median	4.40	14.10	7.80	9.40
	Std. Dev.	74.99	63.48	58.36	67.72
Mkt Cap on Loan (%)	Mean	2.90	5.60	6.22	6.20
	Median	1.84	3.54	4.66	4.90
	Std. Dev.	3.07	4.19	4.39	4.52
Free Float on Loan(%)	Mean	4.68	9.82	10.77	10.66
	Median	2.70	6.75	7.76	7.93
	Std. Dev.	5.68	7.93	9.05	9.04
Panel B. Stock Liquidity					
Turnover by shares (in millions)	Mean	3.24	0.45	1.21	1.94
	Median	0.31	0.10	0.16	0.26
	Std. Dev.	15.74	2.10	3.82	5.35
Free Float (%)	Mean	66.54	65.34	66.07	66.64
	Median	69.00	65.00	68.00	69.00
	Std. Dev.	21.64	21.64	20.00	20.42
Panel C. Other Stock Characteristics					
Volatility	Mean	0.24	0.25	0.24	0.25
	Median	0.22	0.22	0.22	0.23
	Std. Dev.	0.14	0.14	0.12	0.12
Mkt Cap (in millions)	Mean	2294	697	983	1574
	Median	370	444	443	499
	Std. Dev.	8485	3740	2980	5093
Book to Market ratio	Mean	0.67	6.21	1.86	1.21
	Median	0.48	0.47	0.55	0.49
	Std. Dev.	37.91	15.36	7.68	5.52
Past Return (%)	Mean	1.93	2.23	1.41	1.49
	Median	1.60	1.67	1.34	1.36
	Std. Dev.	8.37	8.72	7.81	7.60

Table 9: Abnormal Returns and Cumulative Abnormal Returns based on Simple Sorts (%)

The Table reports abnormal returns and cumulative abnormal returns (CAR) for higher-percentile DCR portfolios from 01 Sep 2003 to 31 May 2007. Stocks are sorted into 99th, 95th, and 90th percentiles based on their Days to Cover Ratio (DCR). Portfolios are re-balanced daily. By skipping one day to avoid concerns about bid-ask bounce, daily abnormal returns, cumulative abnormal returns and t-statistics are calculated using a calendar-time approach with a holding period of 1, 5, 10, 20, and 60 trading days. All returns are quoted as percentages.

		99th Percentile	95th Percentile	90th Percentile
AR(+1)	Mean	0.034	0.020	0.027
	t-Stat	1.345	1.720 *	2.429
CAR(+5)	Mean	0.127	0.127	0.116
	t-Stat	1.188	2.710 ***	2.951 ***
CAR(+10)	Mean	0.291	0.307	0.263
	t-Stat	1.032	3.250 ***	3.423 ***
CAR(+20)	Mean	0.348	0.562	0.622
	t-Stat	1.742 *	2.989 ***	4.265 ***
CAR(+60)	Mean	2.027	1.203	1.463
	t-Stat	1.682 *	1.970 **	3.419 ***

Note: * indicates significance at 10% level, ** indicates significance at 5% level, and *** indicates significance at 1% level.

Table 10: Portfolios based on Double Sorts

This table reports the characteristics of portfolios sorted according to both Days to Cover Ratio (DCR) and exceptional decreases in the percentage of free float on loan over the period 01 September 2003 to 31 May 2007. DCR is calculated as shares on loan divided by average daily trading volume. Exceptional decreases in free float on loan are identified as described in the Methodology section. For each percentile, the column 'All' shows variables for all stocks in that percentile group based on a simple sort; the Crowded Exits column reports portfolios which have a high DCR combined with exceptional falls in short interest, as defined in the Methodology section. Past Return is calculated as the raw percentage return of each portfolio over the previous 20 trading days.

First Sort (By DCR)		**99th Percentile**		**95th Percentile**		**90th Percentile**	
Second Sort (By Exceptional Change)		**All**	**Crowded Exits**	**All**	**Crowded Exits**	**All**	**Crowded Exits**
Panel A. Short Interest							
DCR (days)	Mean	147.26	91.43	52.87	36.55	34.71	25.76
	Median	62.68	57.30	25.76	24.56	19.36	18.58
	Std. Dev.	224.63	94.80	119.21	48.08	86.97	34.74
Shares on Loan	Mean	25.90	27.70	26.31	33.41	33.17	45.37
(in millions)	Median	14.10	18.90	7.80	15.70	9.40	16.60
	Std. Dev.	63.48	24.54	58.36	57.53	67.72	84.69
Mkt Cap on Loan (%)	Mean	5.60	4.51	6.22	6.73	6.20	6.73
	Median	3.54	2.98	4.66	5.90	4.90	5.90
	Std. Dev.	4.19	3.87	4.39	4.58	4.52	4.53
Free Float on Loan(%)	Mean	9.82	7.89	10.77	12.02	10.66	12.11
	Median	6.75	3.63	7.76	9.91	7.93	9.90
	Std. Dev.	7.93	7.48	9.05	9.74	9.04	9.73
Panel B. Stock Liquidity							
Turnover by shares	Mean	454.9	0.4	1206.1	1.7	1936.7	3.0
(in millions)	Median	103.2	0.1	161.9	0.3	260.7	0.5
	Std. Dev.	2096	899	3823	3908	5346	8116
Free Float (%)	Mean	65.34	67.21	66.07	64.56	66.64	64.64
	Median	65.00	71.00	68.00	66.00	69.00	67.00
	Std. Dev.	21.64	23.05	20.00	20.82	20.42	21.22
Panel C. Other Stock Characteristics							
Volatility	Mean	0.25	0.27	0.24	0.25	0.25	0.25
	Median	0.22	0.21	0.22	0.22	0.23	0.23
	Std. Dev.	0.14	0.19	0.12	0.14	0.12	0.12
Mkt Cap	Mean	696.8	642.7	982.8	1257.5	1573.8	1953.6
	Median	444.0	497.0	443.0	503.0	499.0	587.0
	Std. Dev.	3740	692	2980	2224	5093	6234
B/M	Mean	6.21	0.11	1.86	0.49	1.21	0.49
	Median	0.47	0.15	0.55	0.46	0.49	0.43
	Std. Dev.	15.36	0.86	7.68	0.59	5.52	0.51
Past Return	Mean	0.022	0.02	0.014	0.02	0.015	0.02
	Median	0.017	0.02	0.013	0.02	0.014	0.02
	Std. Dev.	0.087	0.08	0.078	0.07	0.076	0.07

Table 11: Abnormal Returns and Cumulative Abnormal Returns based on Double Sorts (in %)

The Table reports mean abnormal returns and cumulative abnormal returns (CAR) for crowded exit portfolios from 01 Sep 2003 to 31 May 2007. For each day, stocks are first sorted into 99th, 95th, and 90th percentiles based on their Days to Cover Ratio (DCR). Within each percentile, stocks showing exceptional decreases in short interest (as defined int he Methodology section) are studied - these stocks are said to experience a 'crowded exit'. For each percentile, the first column reports the abnormal returns for stocks experiencing a crowded exit. The second column reports the difference in mean returns between portfolios of stocks experiencing crowded exits and those that do not experience crowded exits. By skipping one day to avoid concerns about bid-ask bounce, daily abnormal returns, cumulative abnormal returns and t-statistics are calculated using a calendar-time approach with a holding period of 1, 5, 10, 20, and 60 trading days. All numbers are quoted as percentages.

		99th Percentile		95th Percentile		90th Percentile	
		Crowded Exits	**Difference**	**Crowded Exits**	**Difference**	**Crowded Exits**	**Difference**
AR(+1)	Mean	0.518	0.233	0.158	0.026	0.151	0.105
	t-Stat	0.915	0.641	2.161 **	0.256	1.332	1.512 *
CAR(+5)	Mean	1.833	0.647	0.404	-0.050	0.402	0.320
	t-Stat	0.862	0.523	1.409	-0.133	0.873	1.157
CAR(+10)	Mean	4.916	4.125	1.005	1.065	1.051	0.986
	t-Stat	2.191 **	1.949 **	2.344 **	0.834	1.773 *	1.611 *
CAR(+20)	Mean	5.254	5.858	3.403	1.869	3.610	1.986
	t-Stat	1.831 *	1.506 *	4.413 ***	1.426 *	2.994 ***	2.012 **
CAR(+60)	Mean	18.930	14.446	5.033	3.022	6.370	3.640
	t-Stat	2.065 **	1.298 *	1.964 **	0.758	1.703 *	1.324 *

Note: * indicates significance at 10% level, ** indicates significance at 5% level, and *** indicates significance at 1%

Table 12: Double Sort Results Adjusted For Arbitrage

The Table reports mean abnormal returns and cumulative abnormal returns (CAR) for crowded exit portfolios from 01 Sep 2003 to 31 May 2007. First, stocks that are experiencing crowded exits are identified based on double sorts. Any company with a convertible bond in its capital structure is identified as being exposed to arbitrage-motivated short-selling. Crowded exit stocks are then seperated into 'non-convertible' portfolios and 'convertible' portfolios. By skipping one day to avoid concerns about bid-ask bounce, daily abnormal returns, cumulative abnormal returns and t-statistics are calculated using a calendar-time approach with a holding period of 1, 5, 10, 20, and 60 trading days. All numbers are quoted as percentages.

		99th Percentile		95th Percentile		90th Percentile	
		non-convertible	convertible	non-convertible	convertible	non-convertible	convertible
AR(+1)	Mean	0.728	-0.451	0.190	0.040	0.167	0.076
	t-Stat	1.117	-1.408	1.295	0.332	1.895 *	1.079
CAR(+5)	Mean	2.350	-0.545	0.494	0.142	0.466	0.108
	t-Stat	0.096	-0.476	0.825	0.285	1.443	0.194
CAR(+10)	Mean	6.106	-0.559	1.327	0.338	1.095	0.721
	t-Stat	2.279 **	-0.319	1.815 *	0.286	2.120 *	1.054
CAR(+20)	Mean	8.083	-7.759	3.763	3.173	3.569	3.197
	t-Stat	2.235 **	-1.831	2.571 **	1.570	3.974 ***	1.920 *
CAR(+60)	Mean	26.981	-18.103	8.312	0.815	5.514	3.526
	t-Stat	2.508 **	-1.423	1.949 *	0.105	1.967 *	0.594

Note: * indicates significant at the 10% level, ** indicates significant at the 5% level, and *** indicates significant at the 1% lev

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